Maximizing Network and Storage Performance for Big Data Analytics

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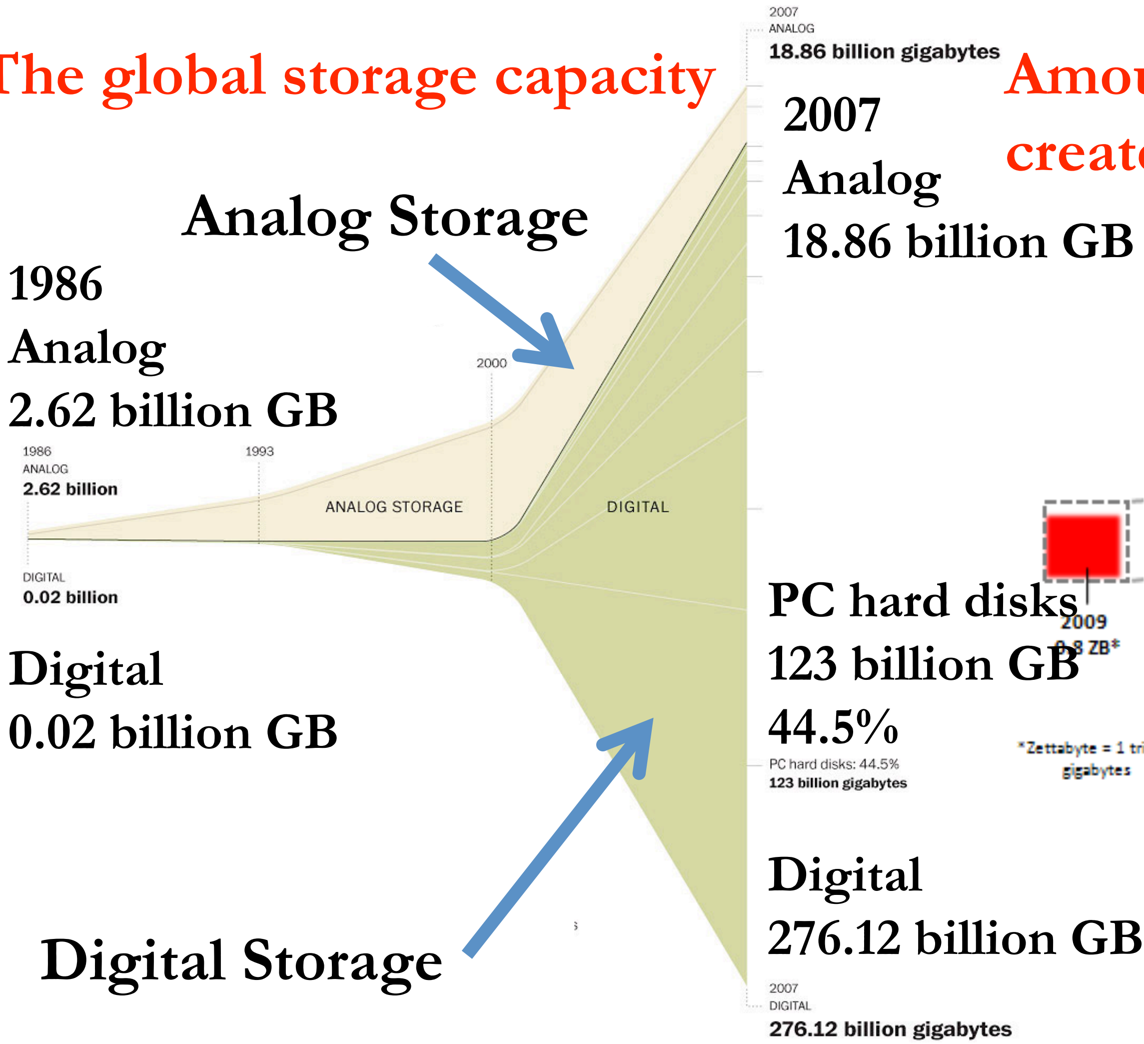
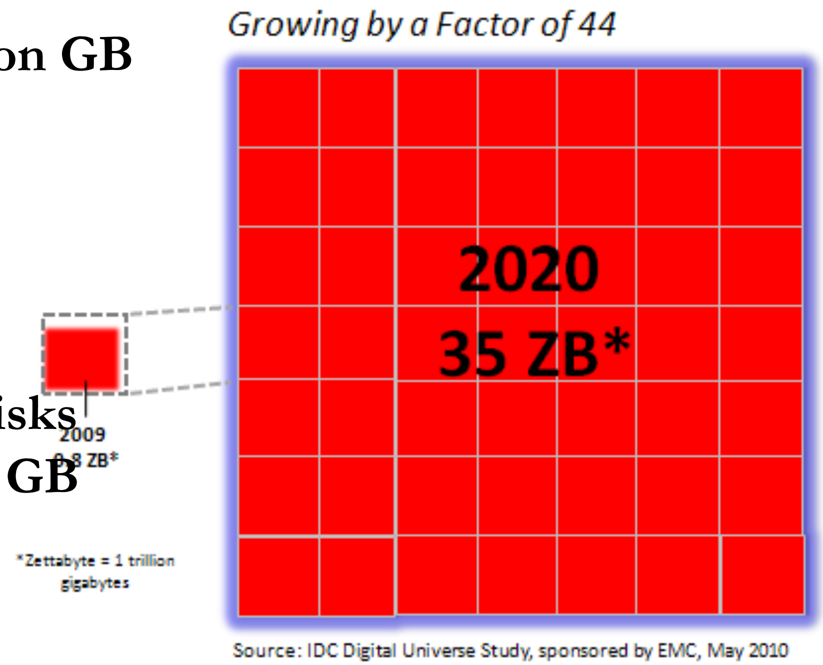
Digital Data Explosion in Human Society

The global storage capacity



Amount of digital information created and replicated in a year



Source:
Exabytes: Documenting the 'digital age' and huge growth in computing capacity,
The Washington Post

Challenge of Big Data Management and Analytics (1)

- **Existing DB technology is not prepared for the huge volume**
  - Until 2007, **Facebook** had a **15TB** data warehouse by a big-DBMS-vendor
  - Now, **~70TB** compressed data added into Facebook data warehouse **every day** (4x total capacity of its data warehouse in 2007)
  - Commercial parallel DBs rarely have **100+** nodes
  - Yahoo!'s Hadoop cluster has **4000+** nodes; Facebook's data warehouse has **2750+** nodes

  - **Typical science and medical research examples:**
    - Large Hadron Collider at **CERN** generates over **15 PB** of data per year
    - Pathology Analytical Imaging Standards databases at Emory reaches **7TB,** going to PB
    - LANL Turbulence Simulation: processing the amount of data at **PB** level.

Challenge of Big Data Management and Analytics (2)

❑ Big data is about all kinds of data

- Online services (social networks, retailers …) focus on big data of online and off-line **click-stream** for deep analytics
- **Medical image** analytics are crucial to both biomedical research and clinical diagnosis

❑ Complex analytics to gain deep insights from big data

- Data mining
- Pattern recognition
- Data fusion and integration
- Time series analysis
- **Goal**: gain deep insights and new knowledge

Challenge of Big Data Management and Analytics (3-4)

- **Conventional database business model is not affordable**
  - Expensive software license
  - High maintenance fees even for open source DBs
  - Store and manage data in a system at least $10,000/TB*
  - In contrast, Hadoop-like systems only cost $1,500/TB**

- **Conventional database processing model is "scale-up" based**
  - Performance improvement relies on CPU/memory/storage/network updates in a dedicated site (**BSP model**, CACM, 1990)
  - Big data processing model is **"scale-out"** based (**DOT model**, SOCC'11): relies on continuously adding low cost computing and storage nodes in a

MapReduce programming model becomes an effective data processing engine for big data analytics

Why MapReduce?

- **A simple but effective programming model designed to process huge volumes of data concurrently**

- **Two unique properties**
  - Minimum dependency among tasks (almost **sharing nothing**)
  - Simple task operations in each node (**low cost machines** are sufficient)

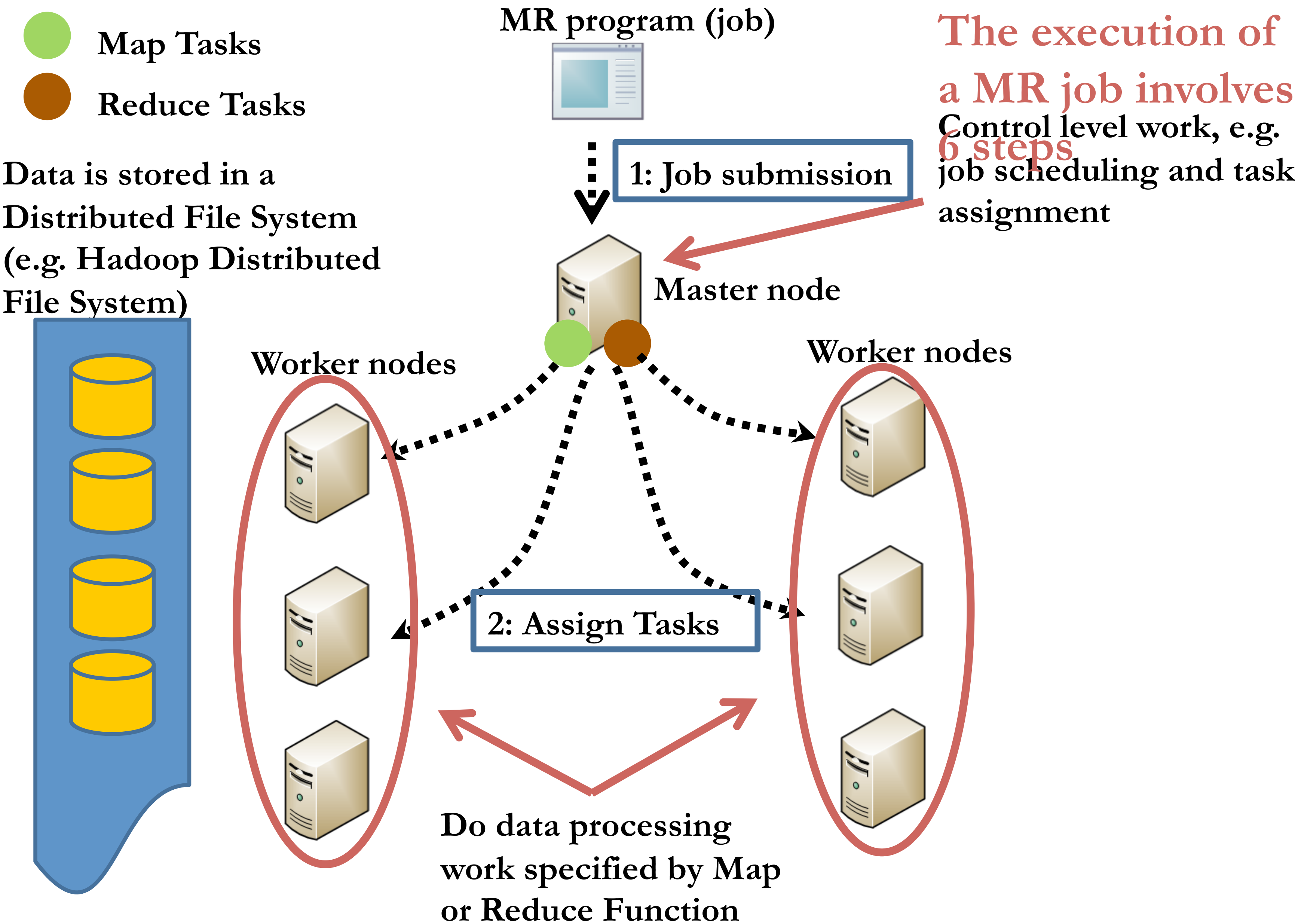
- **Two strong merits for big data anaytics**
  - **Scalability** (Amadal's Law): increase throughput by increasing # of nodes
  - **Fault-tolerance** (quick and low cost recovery of the failures of tasks)

- **Hadoop is the most widely used implementation of MapReduce**
  - in hundreds of society-dependent corporations/organizations for big data analytics: **AOL, Baidu**, **EBay**, **Facebook**, **IBM**, **NY Times**, **Yahoo!** ….

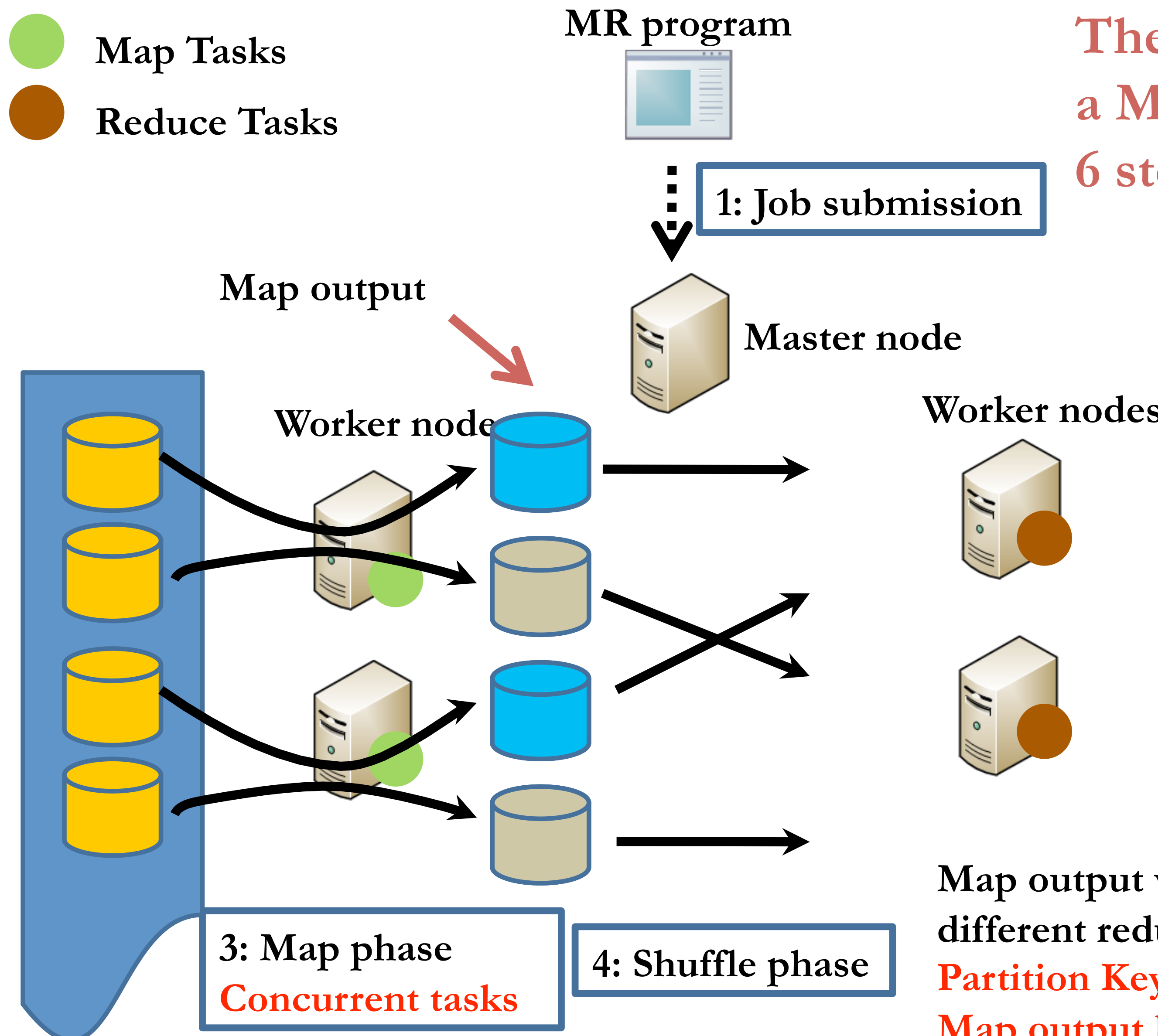
MapReduce Overview

- **The basic framework comes from functional programming: simple key/value pairs forms a chain of MR execution**
- **Map: (k1, v1) → (k2, v2)**
- **Reduce: (k2, v2) → (k3, v3)**
- **Shuffle: Partition Key (It could be the same as k2, or not)**
  - Partition Key: to determine how a key/value pair in the map output be transferred to a reduce task

MR(Hadoop) Job Execution Insights



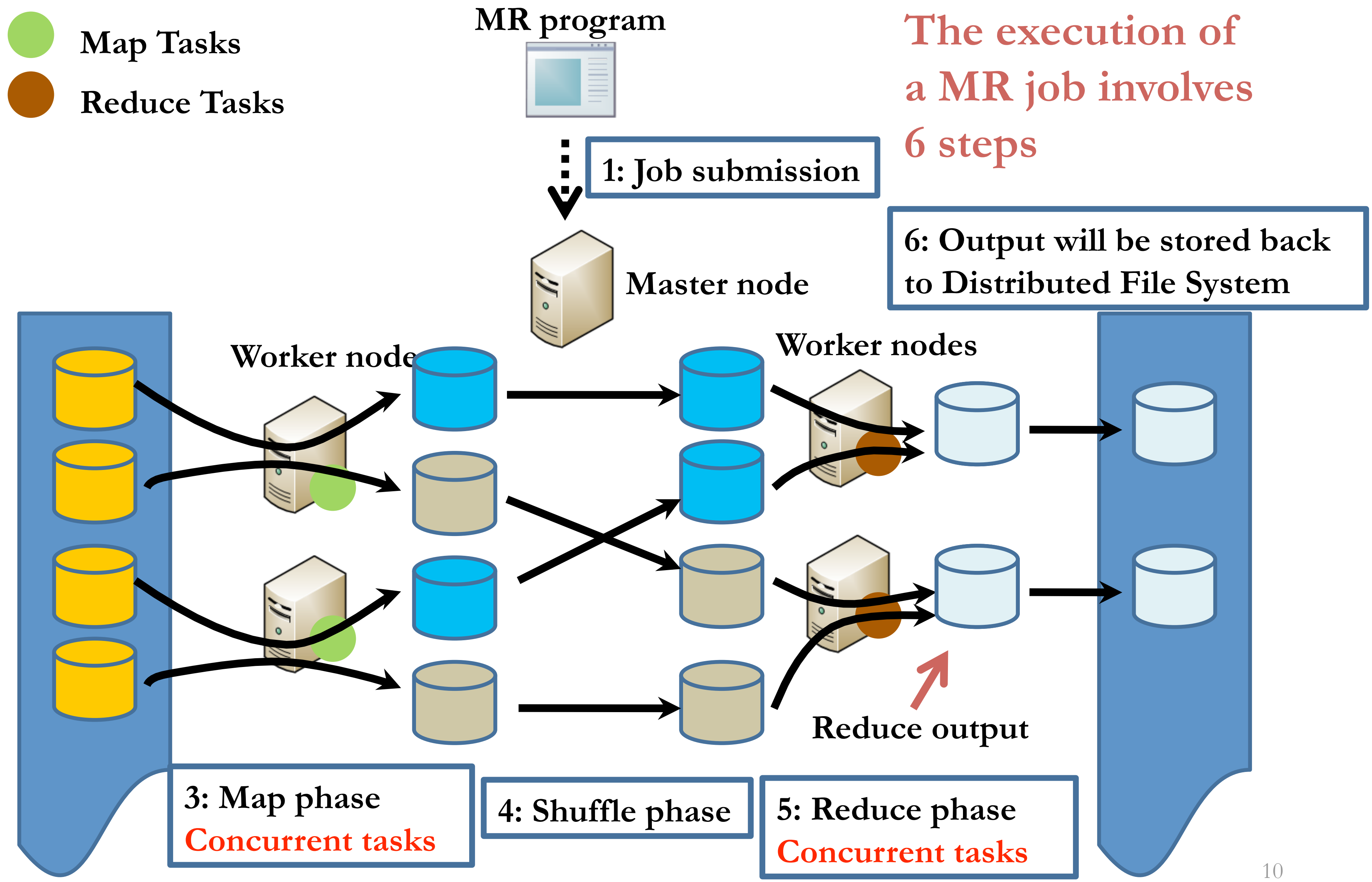
MR(Hadoop) Job Execution Insights



The execution of a MR job involves 6 steps

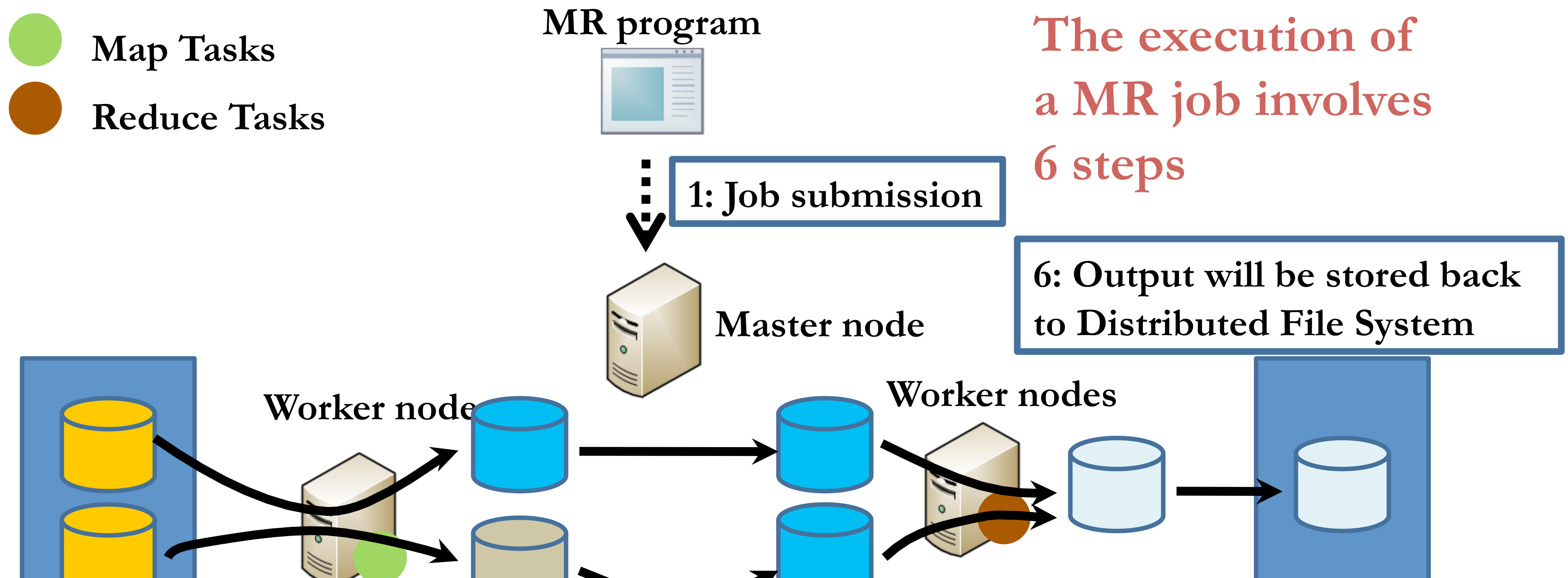
Map output will be shuffled to different reduce tasks based on Partition Keys (PKs) (usually Map output keys)

MR(Hadoop) Job Execution Insights



MR(Hadoop) Job Execution Insights

The execution of a MR job involves 6 steps



A MapReduce (MR) job is highly resource-consuming:

1: Input data scan in the Map phase => local or remote I/Os

2: Store intermediate results of Map output => local I/Os

3: Transfer data across in the Shuffle phase => network costs

4: Store final results of this MR job => local I/Os + network costs (replicate data)

Two Critical Challenges in Production Systems

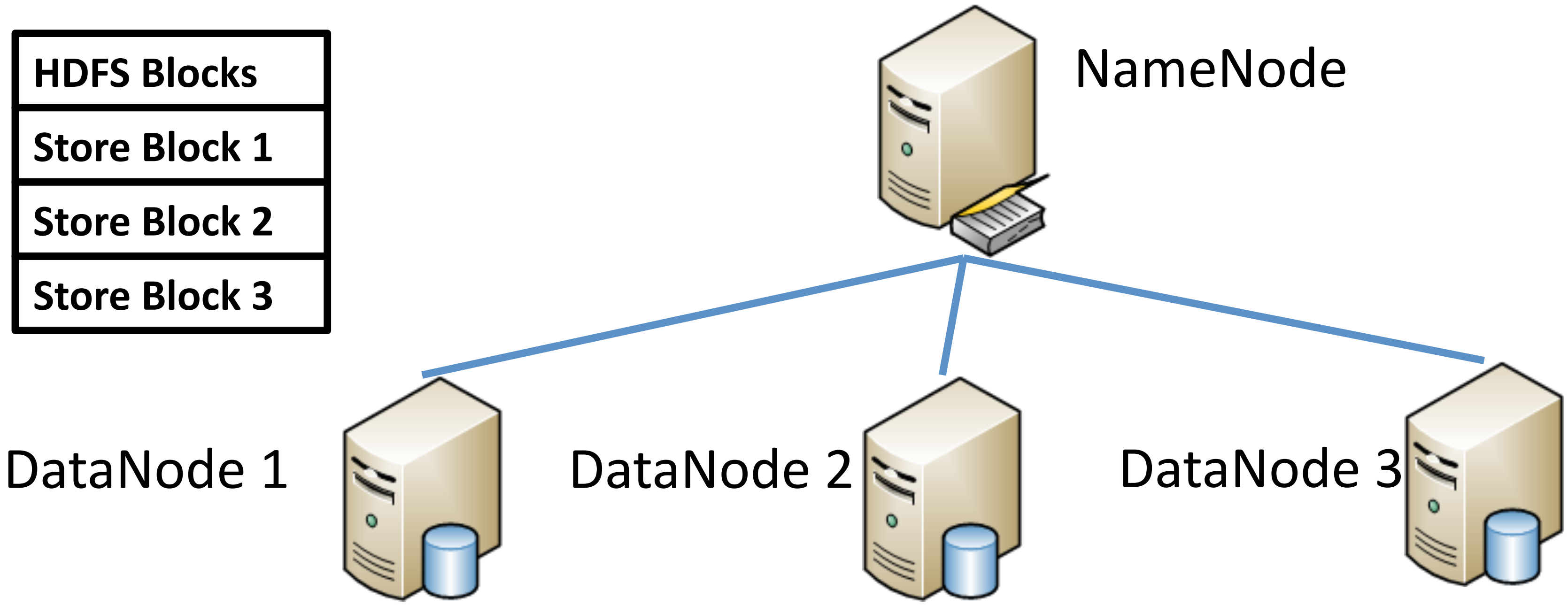
- **Background: Standard Relational Databases have been moved to MapReduce Environment, such as Hive and Pig by Facebook and Yahoo!**
- **Challenge 1: How to initially store big data in distributed systems**
  - **Objective:** to minimize network and storage costs for massive accesses
- **Challenge 2: How to automatically convert relational database queries into MapReduce jobs**
  - **Objectives:** to minimize network and storage costs for MR job execution
- **Addressing these two Challenges, we aim to achieve**
  - **High performance of big data analytics**
  - **High productivity of big data analytics**

Challenge 1: Fast and Storage-efficient Data Placement

- **Data loading (L)**
  - the overhead of writing data to distributed files ystem and local disks
- **Query processing (P)**
  - local storage bandwidths of query processing
  - the amount of network transfers
- **Storage space utilization (S)**
  - Data compression ratio
  - The convenience of applying efficient compression algorithms
- **Adaptivity to dynamic workload patterns (W)**
  - Additional overhead on certain queries

➢**Objective: to design and implement a data placement structure meeting these requirements in MapReduce-based data warehouses**

Initial Stores of Big Data in Distributed Environment



- ❑ **HDFS (Hadoop Distributed File System) blocks are distributed**
- ❑ **Users have a limited ability to specify customized data placement policy**
  - e.g. to specify which blocks should be co-located
- ❑ **Minimizing I/O costs in local disks and intra network communication**

MR programming is not that "simple"!

```
package tpch;
import java.io.IOException;
import java.util.ArrayList;
import org.apache.hadoop.conf.Configuration;
import org.apache.hadoop.conf.Configured;
...
import org.apache.hadoop.util.GenericOptionsParser;
import org.apache.hadoop.util.Tool;
...
        inputFile = ((FileSplit)context.getInputSplit()).
        if (inputFile.compareTo("lineitem.tbl") == 0){
            isLineitem = true;
```

```
public static class Reduce extends Reducer<IntWritable,Text,IntWritable,Text> {
        private Text result = new Text();

        public void reduce(IntWritable key, Iterable<Text> values,
                           Context context
                ) throws IOException, InterruptedException {

                    double sumQuantity = 0.0;
                    IntWritable newKey = new IntWritable();
...
                }
                else
...
                context.write(newKey, result);
            }
        }
...
        public static void main(String[] args) throws Exception {
            int res = ToolRunner.run(new Configuration(), new Q18Job1(), args);
            System.exit(res);
        }
}
```

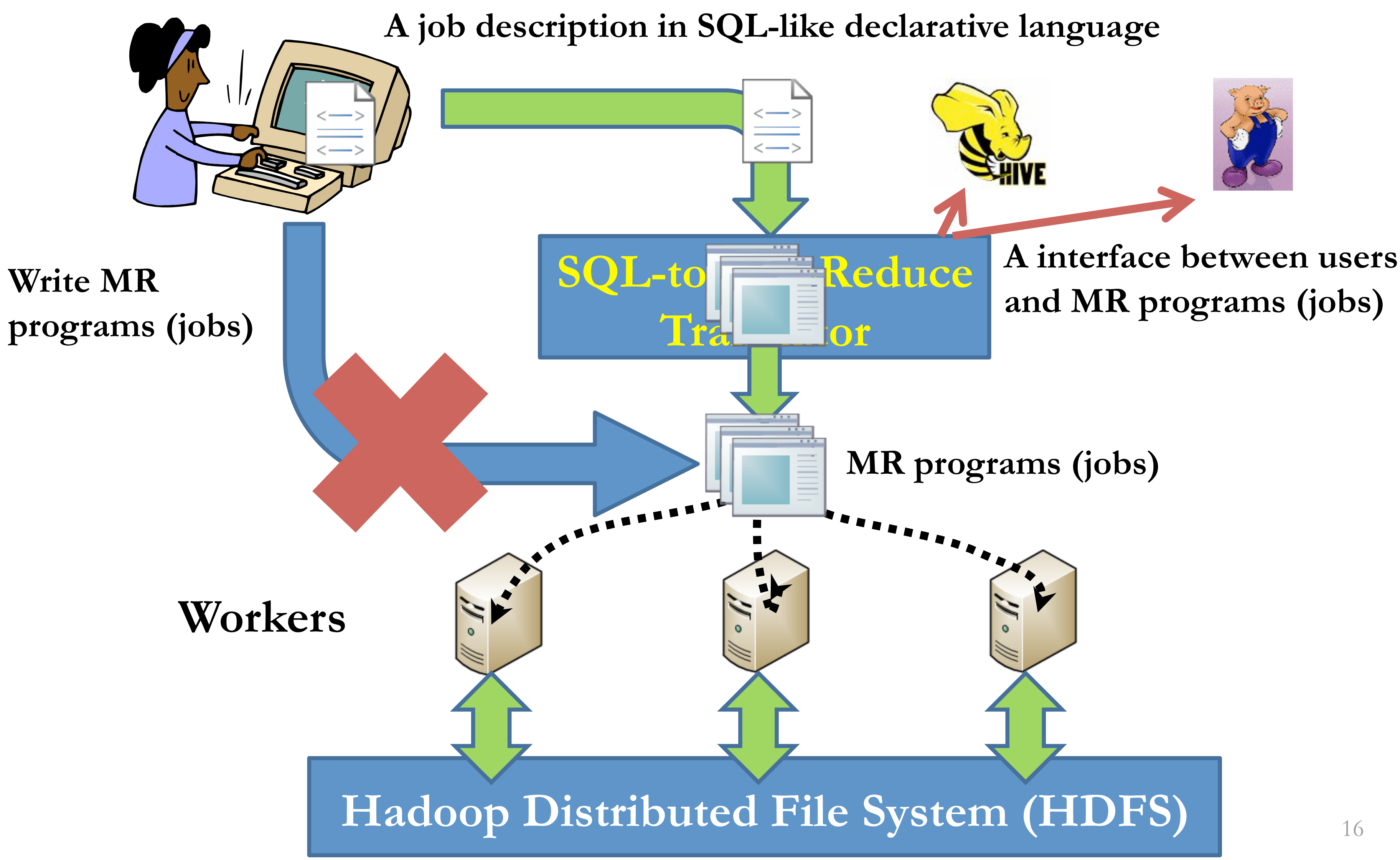
This complex code is for a simple MR job

Low Productivity!

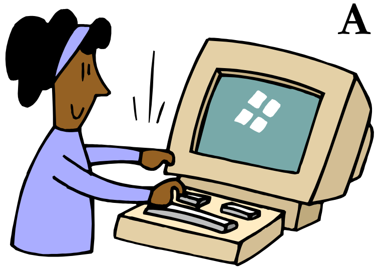
Do you miss some thing like …

"SELECT * FROM Book WHERE price > 100.00"?

Challenge 2: High Quality MapReduce in Automation



Challenge 2: High Quality MapReduce in Automation



A job description in SQL-like declarative language

Write MR programs (jobs)

SQL-to-MapReduce Translator

A interface between users and MR programs (jobs)

A data warehousing system **(Facebook)**

A high-level programming environment **(Yahoo!)**

Improve productivity from hand-coding MapReduce programs

- **95%+** Hadoop jobs in Facebook are generated by **Hive**
- **75%+** Hadoop jobs in Yahoo! are invoked by **Pig***

* http://hadooplondon.eventbrite.com/

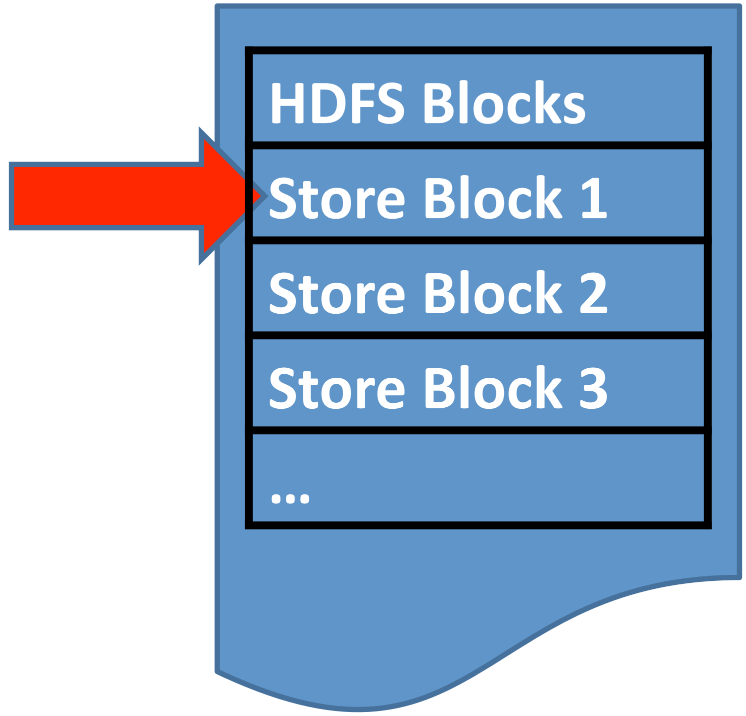
Outline

- **RCFile: a fast and space-efficient placement structure**
  - Re-examination of existing structures
  - A Mathematical model as basis of RCFile
  - Experiment results
- **Ysmart: a high efficient query-to-MapReduce translator**
  - Correlations-aware is the key
  - Fundamental Rules in the translation process
  - Experiment results
- **Impact of RCFile and Ysmart in production systems**
- **Conclusion**

Row-Store: Merits/Limits with MapReduce

Table

A	B	C	D
101	201	301	401
102	202	302	402
103	203	303	403
104	204	304	404
105	205	305	405

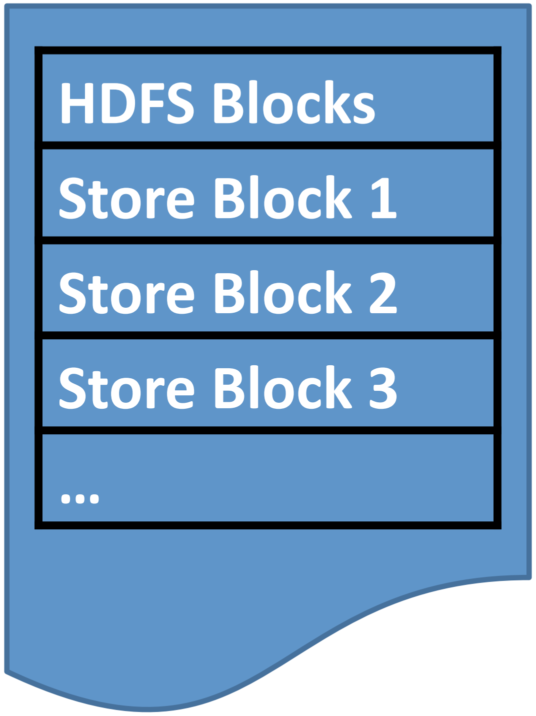


- Data loading is fast (no additional processing);
- All columns of a data row are located in the same HDFS block
- Not all columns are used (unnecessary storage bandwidth)
- Compression of different types may add additional overhead

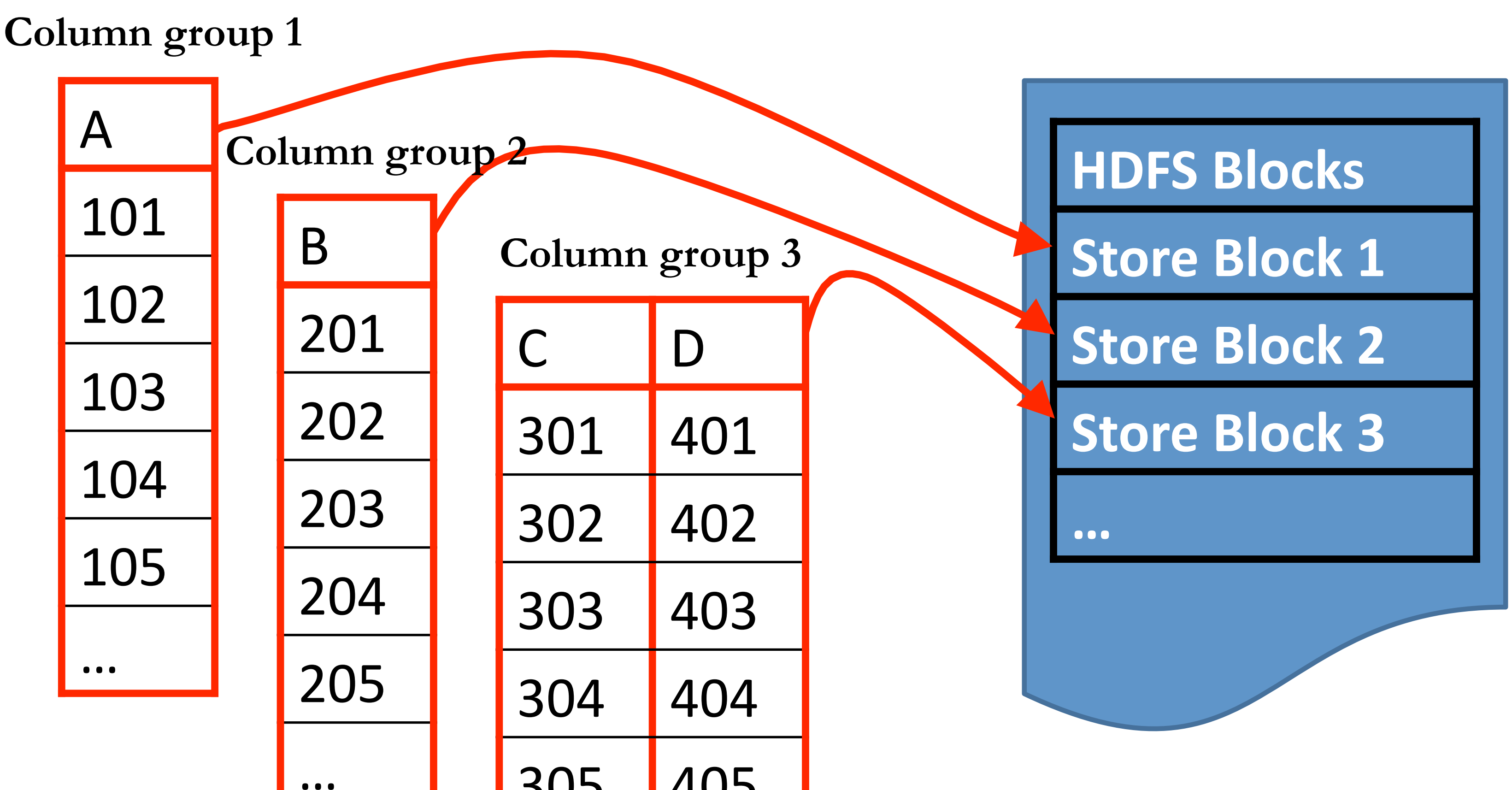
Column-Store: Merits/Limits with MapReduce

Table

A	B	C	D
101	201	301	401
102	202	302	402
103	203	303	403
104	204	304	404
105	205	305	405
…	…	…	…



Column-Store: Merits/Limits with MapReduce



- ➢Unnecessary I/O costs can be avoided: Only needed columns are loaded, and easy compression
- ➢Additional network transfers for column grouping

Optimization of Data Placement Structure

- **Consider four processing requirements comprehensively**
- **The optimization problem in systems design becomes:**
  - In a environment of **dynamic workload (W)** and with a **suitable data compression algorithm (S)** to improve the utilization of data storage,

    find a data placement structure **(DPS)** that minimizes the processing time of a basic operation **(OP)** on a table **(T)** with ***n*** columns
- **Two basic operations**
  - **Write:** the essential operation of **data loading (L)**
  - **Read:** the essential operation of **query processing (P)**

Finding Optimal Data Placement Structure

$$E(read \mid DPS) =$$

$$\sum_{i=1}^{n} \sum_{j=1}^{\binom{n}{i}} f(i,j,n)\left(\frac{S}{B_{local}} \times \frac{1}{\rho} \times \alpha(DPS) + \lambda(DPS,i,j,n) \times \frac{S}{B_{netwotk}} \times \frac{i}{n}\right)$$

	Row-Store	Column-store	**Ideal**
Read efficiency	**1**	i/n (*optimal*)	i/n (*optimal*)
Communication overhead	**0** (*optimal*)	β $(0\% \leq \beta \leq 100\%)$	**0** (*optimal*)

Can we find a Data Placement Structure with both optimal *read efficiency* and *communication overhead* ?

Goals of RCFile

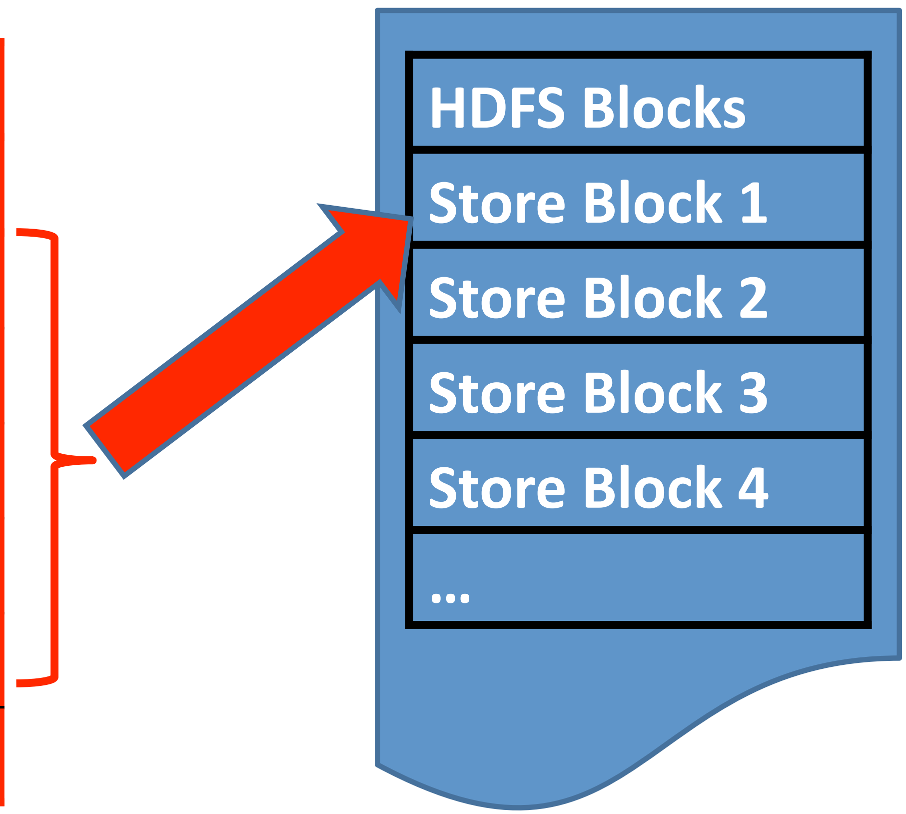
- ❑ **Eliminate unnecessary I/O costs like Column-store**
  - Only read needed columns from disks
- ❑ **Eliminate network costs in row construction like Row-store**
- ❑ **Keep the fast data loading speed of Row-store**
- ❑ **Can apply efficient data compression algorithms conveniently like Column-store**
- ❑ **Eliminate all the limits of Row-store and Column-store**

RCFile: Partitioning a Table into Row Groups

A HDFS block consists of one or multiple row groups

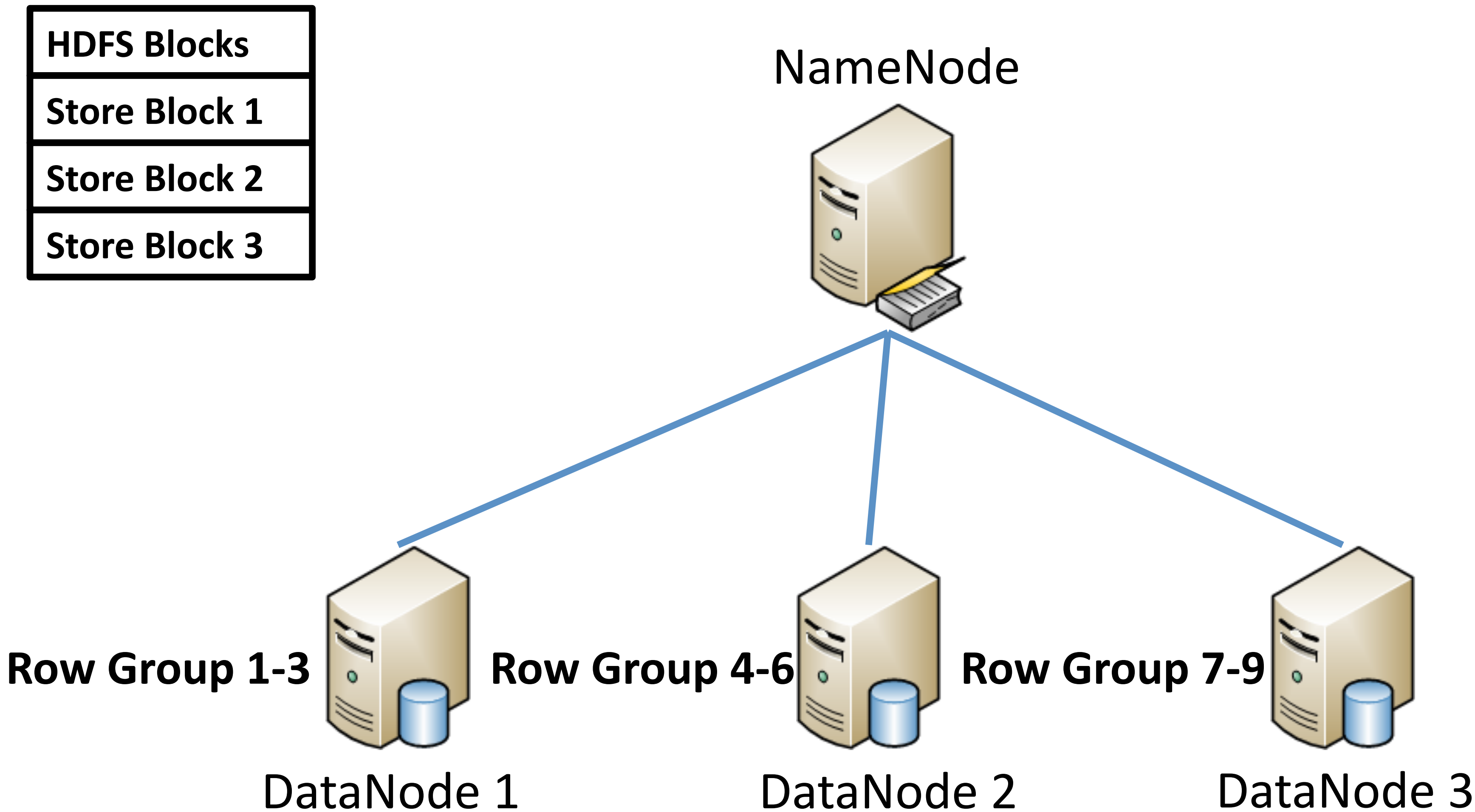
Table

A	B	C	D
…	A.Row	Group	…
101	201	301	401
102	202	302	402
103	203	303	403
104	204	304	404
105	205	305	405
…	…	…	…



RCFile: Distributed Row-Group Data among Nodes

For example, each HDFS block has three row groups



Inside a Row Group

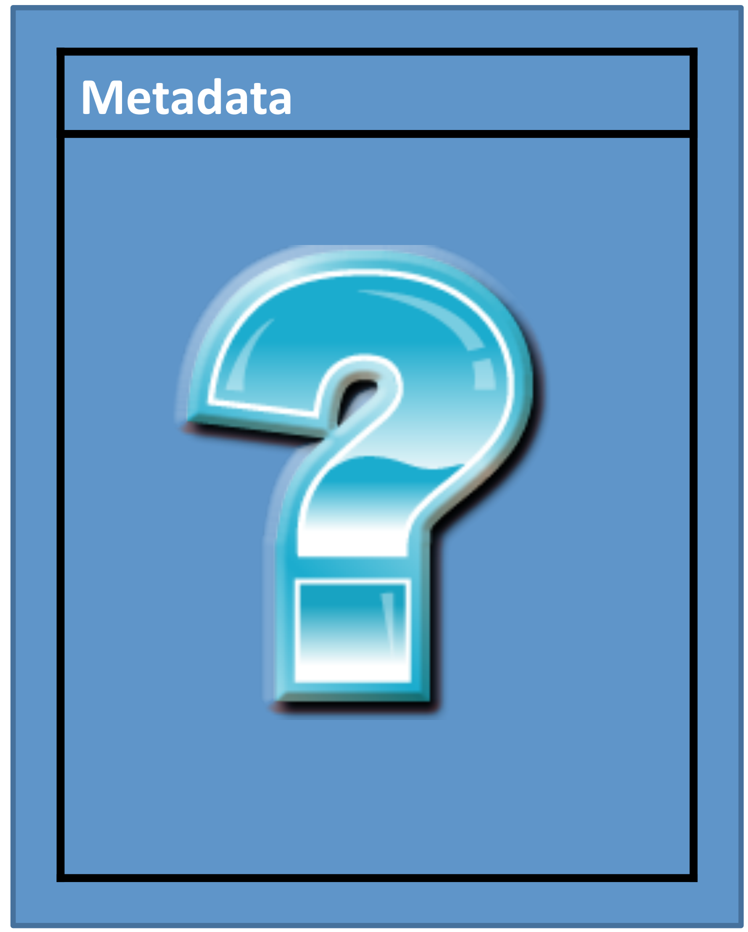
Store Block 1

101	201	301	401
102	202	302	402
103	203	303	403
104	204	304	404
105	205	305	405

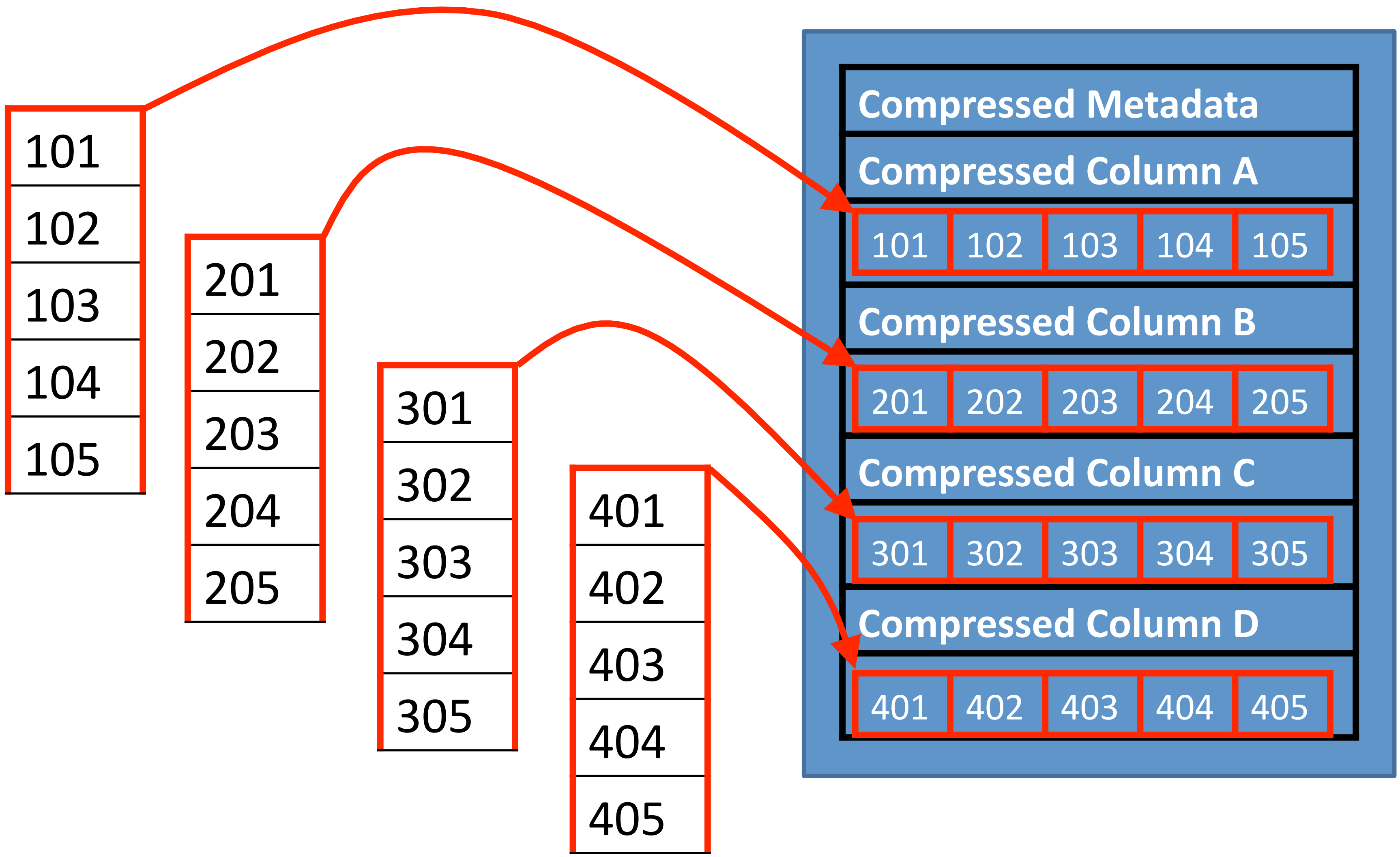
Metadata

Inside a Row Group

101	201	301	401
102	202	302	402
103	203	303	403
104	204	304	404
105	205	305	405



RCFile: Inside each Row Group



Benefits of RCFile

- **Eliminate unnecessary I/O costs**
  - In a row group, table is partitioned by columns
  - Only read needed columns from disks
- **Eliminate network costs in row construction**
  - All columns of a row are located in the same HDFS block
- **Comparable data loading speed to Row-Store**
  - Only adding a vertical-partitioning operation in the data loading procedure of Row-Store
- **Can apply efficient data compression algorithms conveniently**
  - Can use compression schemes used in Column-store

Expected Time of a Read Operation

$$E(read \mid DPS) =$$

$$\sum_{i=1}^{n} \sum_{j=1}^{\binom{n}{i}} f(i,j,n)\left(\frac{S}{B_{local}} \times \frac{1}{\rho} \times \alpha(DPS) + \lambda(DPS,i,j,n) \times \frac{S}{B_{netwotk}} \times \frac{i}{n}\right)$$

	Row-Store	Column-store
Read efficiency	**1**	i/n (*optimal*)
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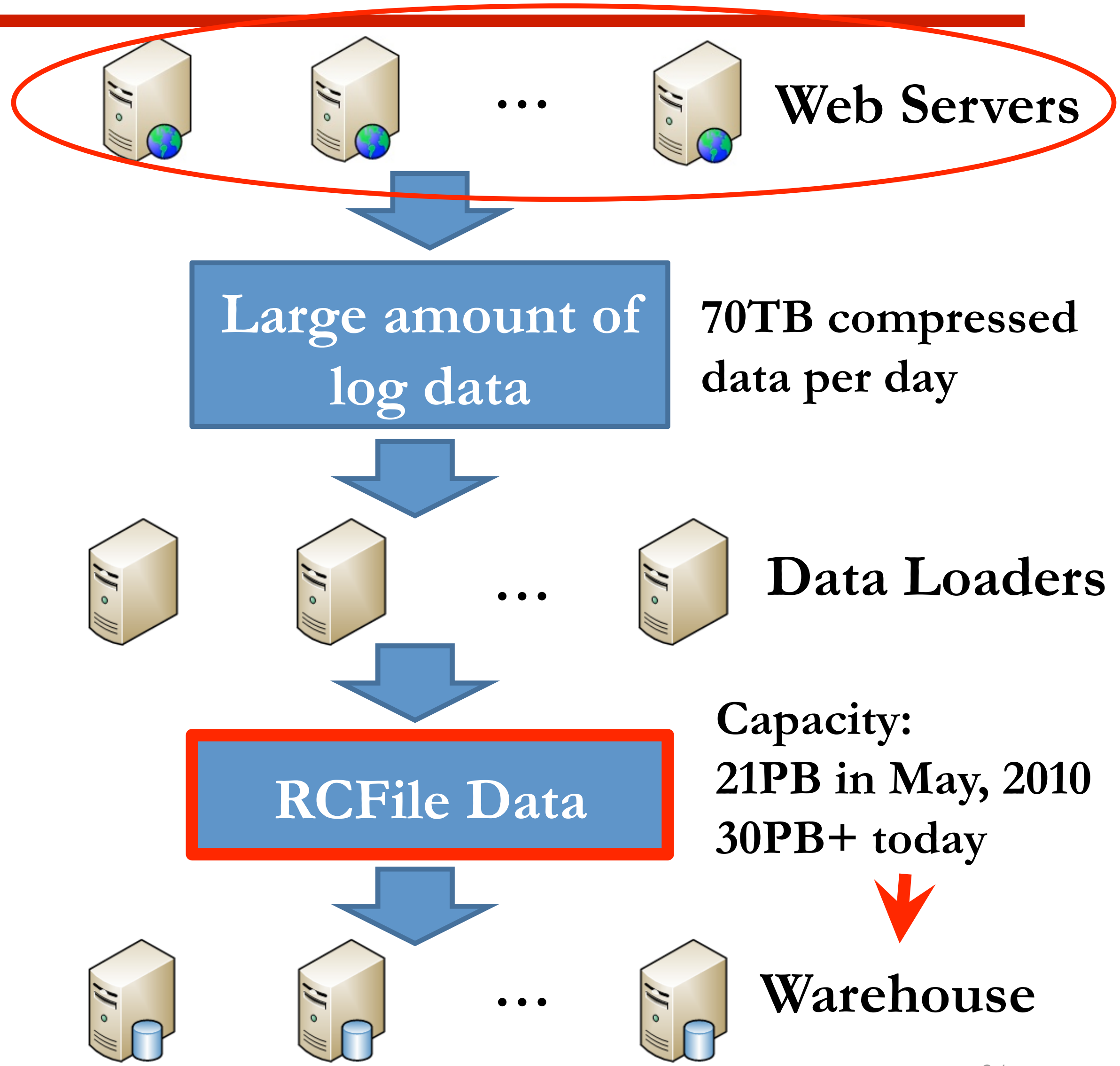
	Row-Store	Column-store	RCFile
Read efficiency	**1**	i/n (*optimal*)	i/n (optimal)
Communication overhead	**0** (*optimal*)	β ($0\% \le \beta \le 100\%$)	**0** (optimal)

Facebook Data Analytics Workloads Managed By RCFile

- **Reporting**
  - E.g. daily/weekly aggregations of impression/click counts
- **Ad hoc analysis**
  - E.g. geographical distributions and activities of users in the world
- **Machine learning**
  - E.g. online advertizing optimization and effectiveness studies
- **Many other data analysis tasks on user behavior and patterns**
- **User workloads and related analysis cannot be published**
- **RCFile evaluation with public available workloads with excellent performance (ICDE'11)**

RCFile in Facebook

The interface to
500+ million users



Picture source: Visualizing Friendships, http://www.facebook.com/notes/facebook-engineering/visualizing-friendships/469716398919

Summary of RCFile

- Data placement structure lays a foundation for MapReduce-based big data analytics
- Our optimization model shows RCFile meets all basic requirements
- RCFile: an operational system for daily tasks of big data analytics
  - A part of **Hive**, a data warehouse infrastructure on top of Hadoop.
  - A default option for **Facebook** data warehouse
  - Has been integrated into **Apache Pig** since version 0.7.0 (expressing data analytics tasks and producing MapReduce programs)
  - **Customized RCFile** systems for special applications
- Refining RCFile and optimization model, making RCFile as a standard data placement structure for big data analytics

Outline

- ❑ ~~RCFile: a fast and space-efficient placement structure~~
  - ~~Re-examination of existing structures~~
  - ~~A Mathematical model as basis of RCFile~~
  - ~~Experiment results~~
- ❑ **Ysmart: a high efficient query-to-MapReduce translator**
  - Correlations-aware is the key
  - Fundamental Rules in the translation process
  - Experiment results
- ❑ **Impact of RCFile and Ysmart in production systems**
- ❑ **Conclusion**

Translating SQL-like Queries to MapReduce Jobs: Existing Approach

- **"Sentence by sentence" translation**
  - [C. Olston et al. SIGMOD 2008], [A. Gates et al., VLDB 2009] and [A. Thusoo et al., ICDE2010]
  - Implementation: Hive and Pig

- **Three steps**
  - **Identify major sentences with operations that shuffle the data**
    - Such as: Join, Group by and Order by
  - **For every operation in the major sentence that shuffles the data, a corresponding MR job is generated**
    - e.g. a join op. => a join MR job
  - **Add other operations, such as selection and projection, into corresponding MR jobs**

Existing SQL-to-MapReduce translators give unacceptable performance.

An Example: TPC-H Q21

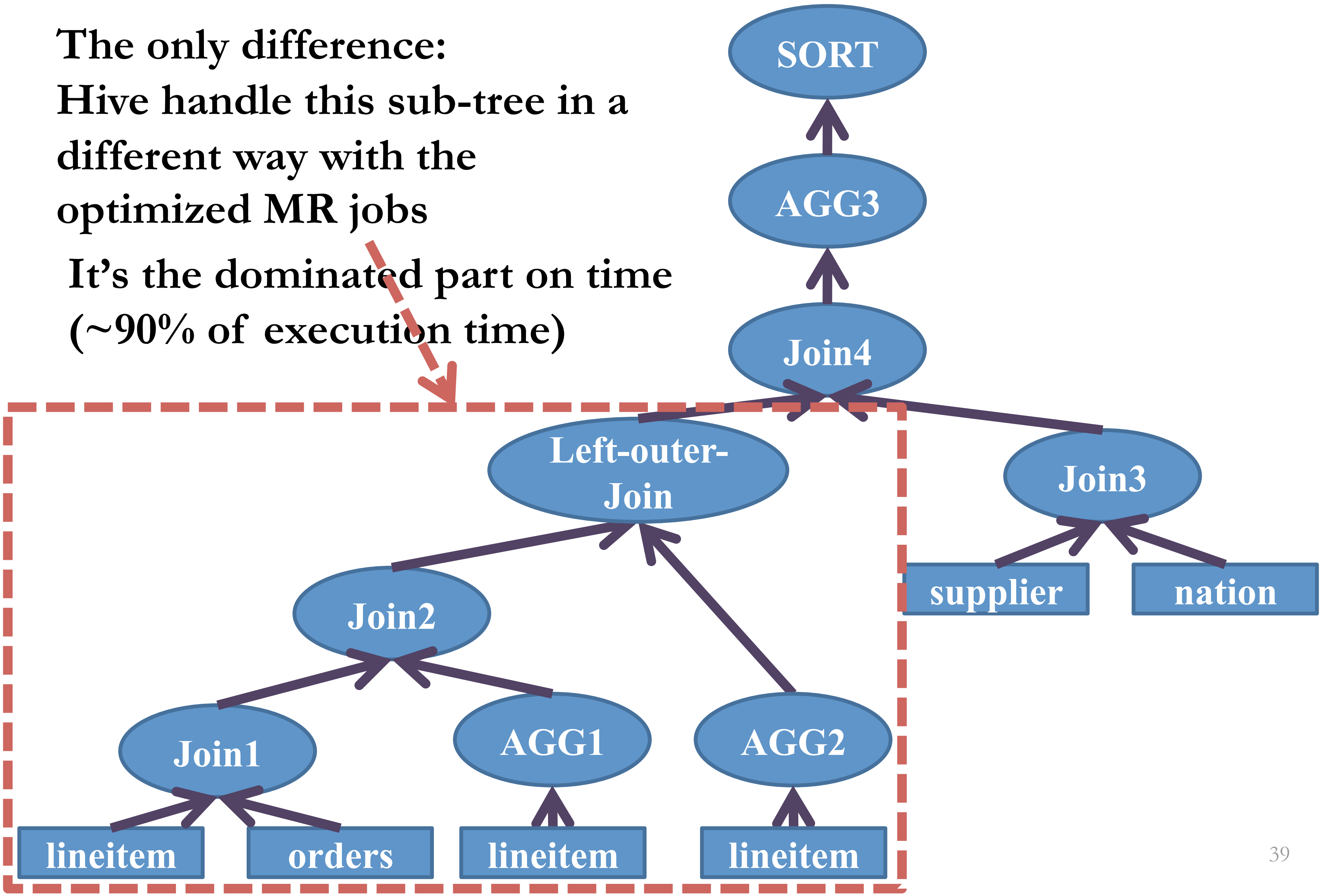
- One of the most complex and time-consuming queries in the TPC-H benchmark for data warehousing performance
- Optimized MR Jobs vs. Hive in a Facebook production cluster

What's wrong?

The Execution Plan of TPC-H Q21

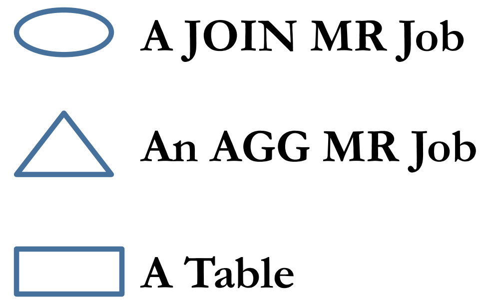
The only difference:
Hive handle this sub-tree in a different way with the optimized MR jobs

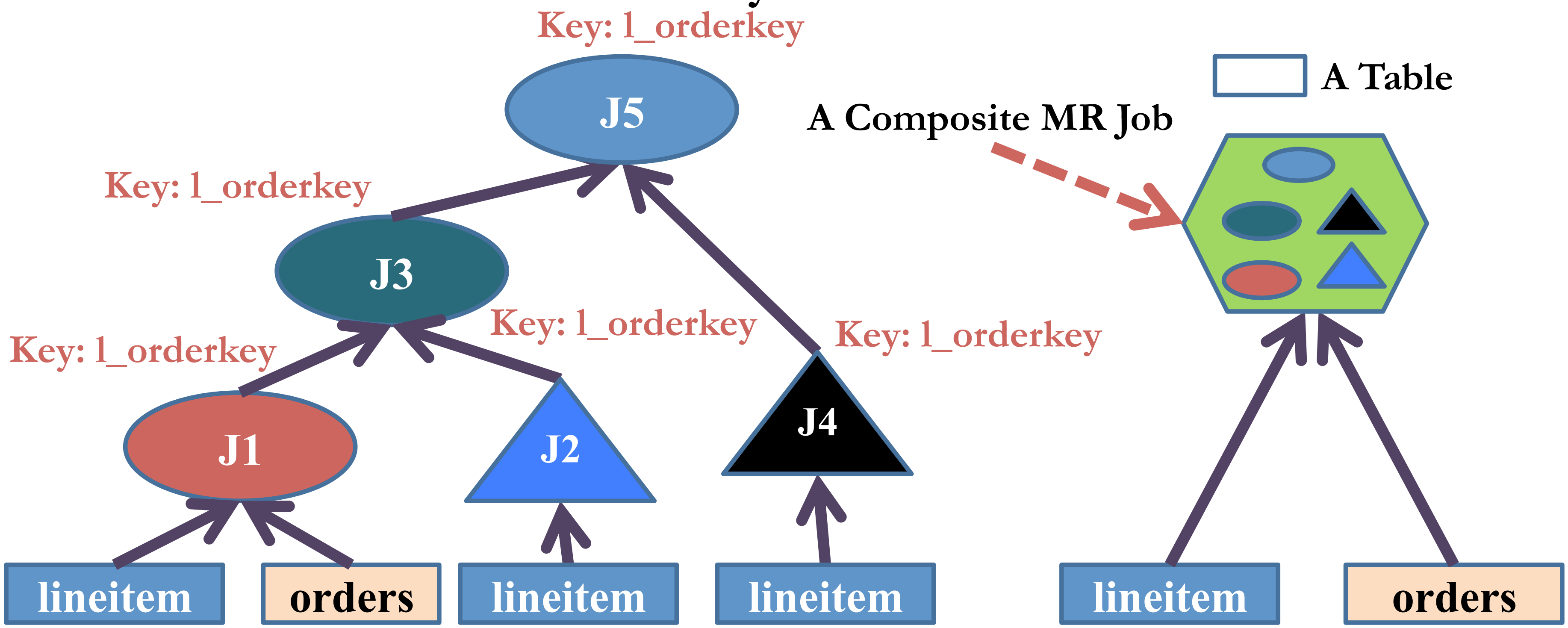
It's the dominated part on time (~90% of execution time)



However, inter-job correlations exist.

Let's look at the Partition Key





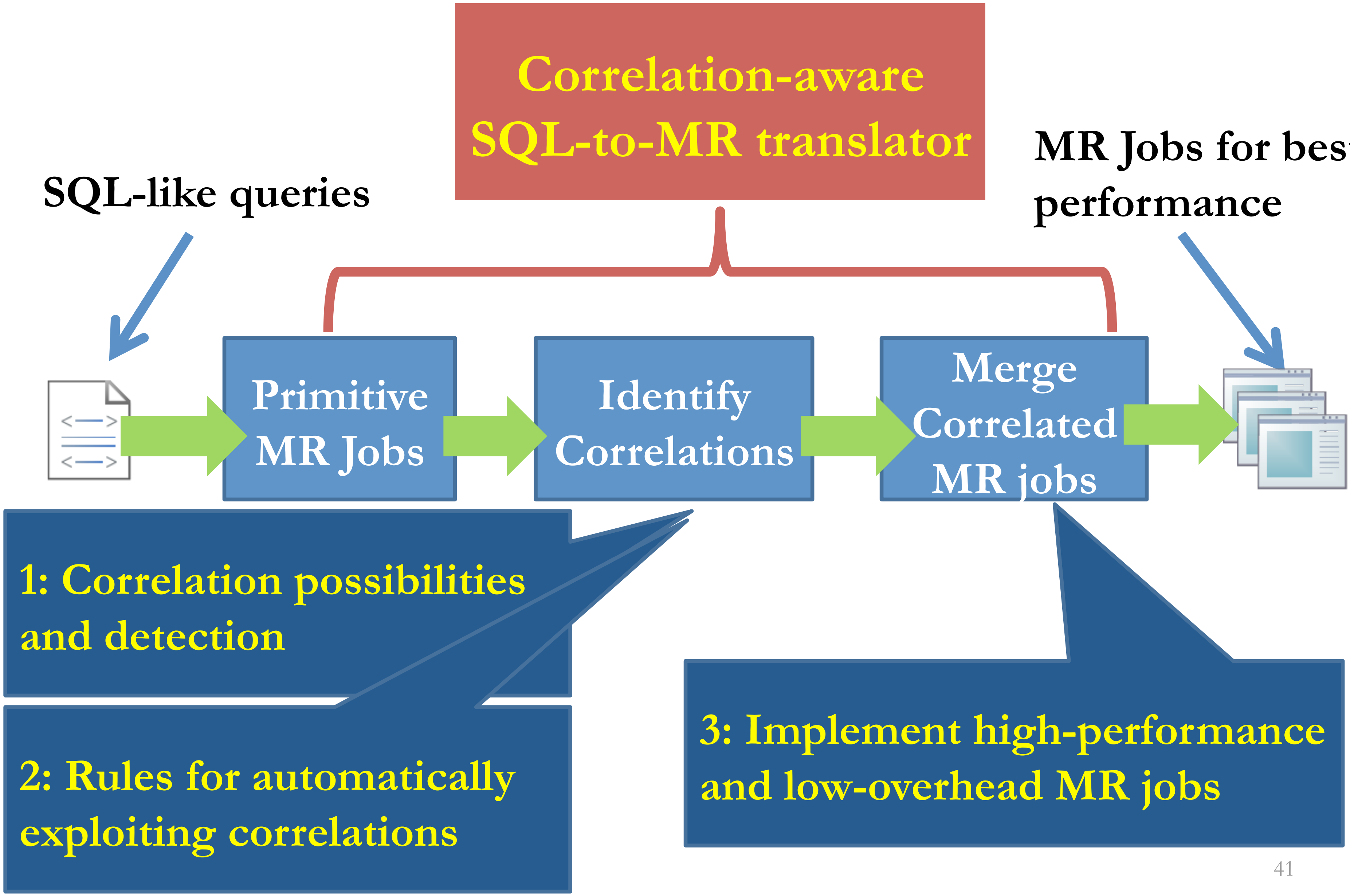
J1 to J5 all use the same partition key 'l_orderkey'

What's wrong with existing SQL-to-MR translators?

Existing translators are correlation-unaware

1. Ignore common data input
2. Ignore common data transition

Our Approaches and Critical Challenges



Query Optimization Rules for Automatically Exploiting Correlations

- Exploiting both Input Correlation and Transit Correlation

- Exploiting the Job Flow Correlation associated with Aggregation jobs

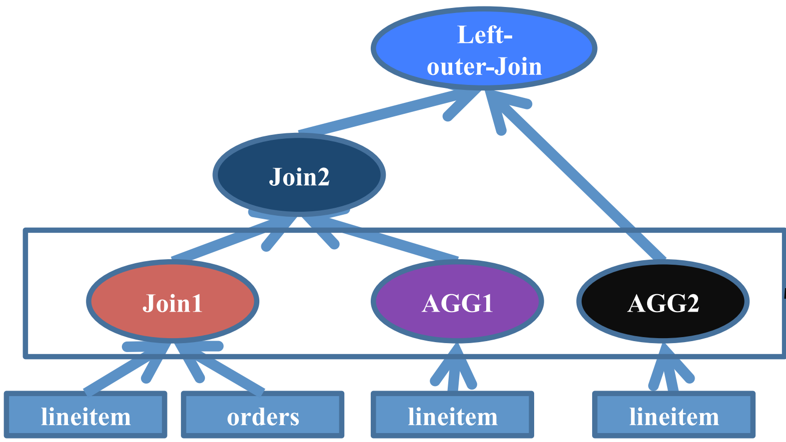
- Exploiting the Job Flow Correlation associated with JOIN jobs and their Transit Correlated parents jobs

- Exploiting the Job Flow Correlation associated with JOIN jobs

Exp1: Four Cases of TPC-H Q21

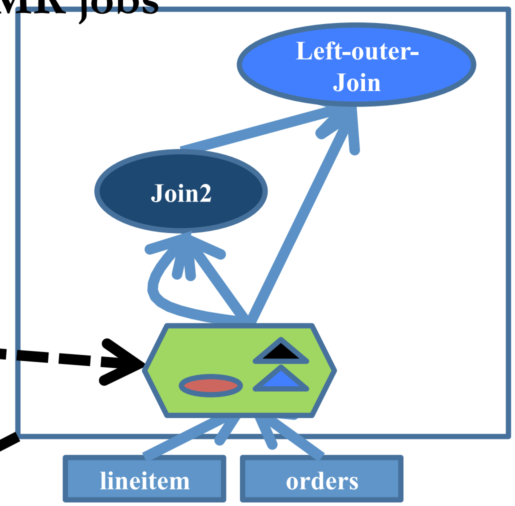
1: Sentence-to-Sentence Translation

- 5 MR jobs



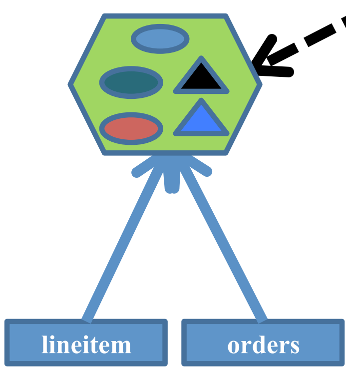
2: InputCorrelation+TransitCorrelation

- 3 MR jobs



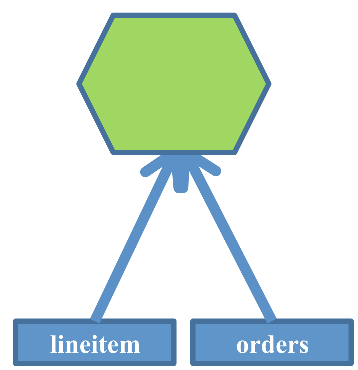
3: InputCorrelation+TransitCorrelation+ JobFlowCorrelation

- 1 MR job

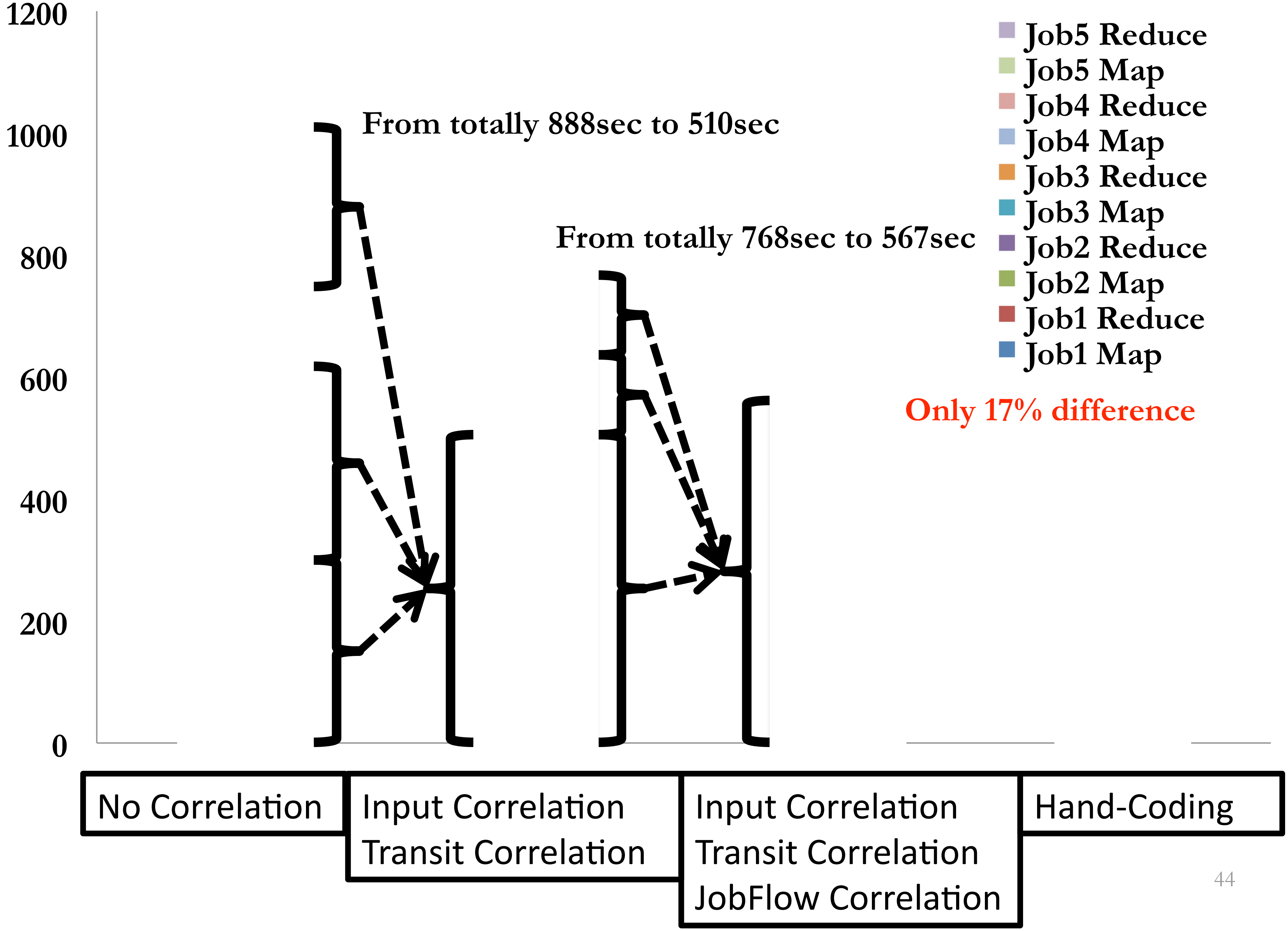


4: Hand-coding (similar with Case 3)

- In reduce function, we optimize code according query semantic

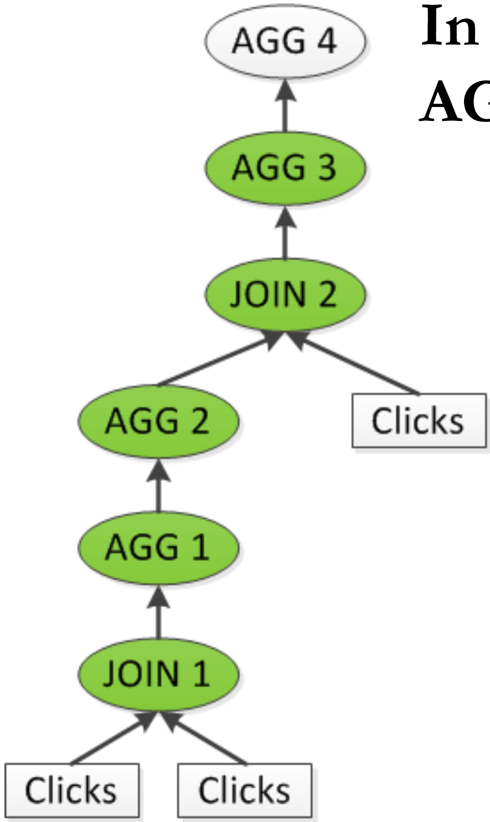


Breakdowns of Execution Time (sec)

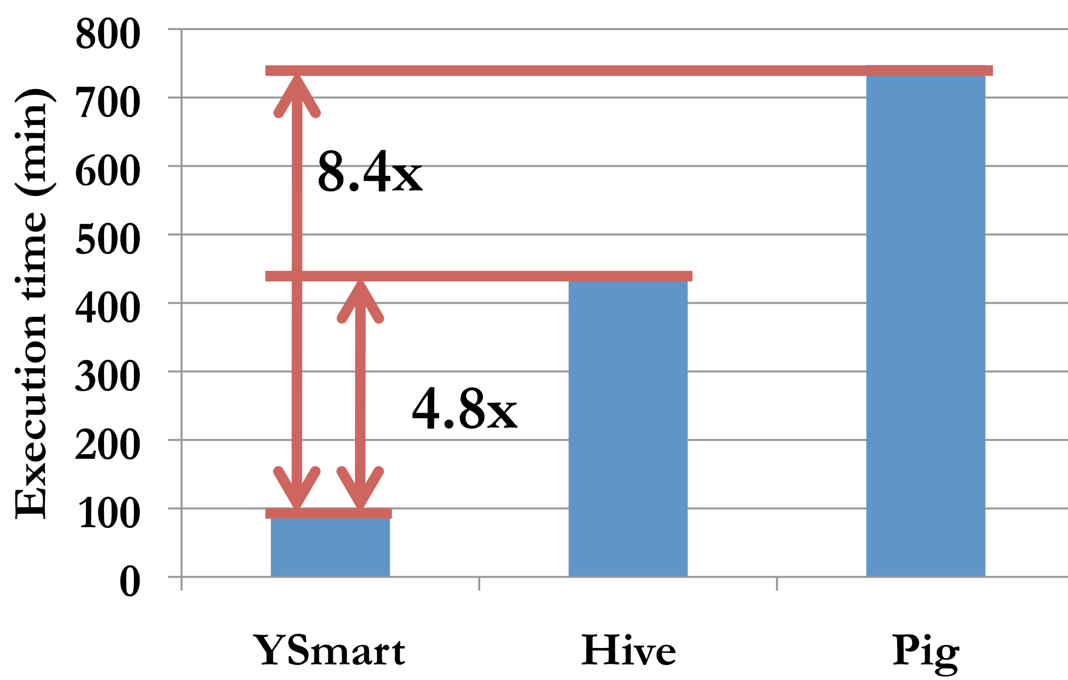


Exp2: Clickstream Analysis

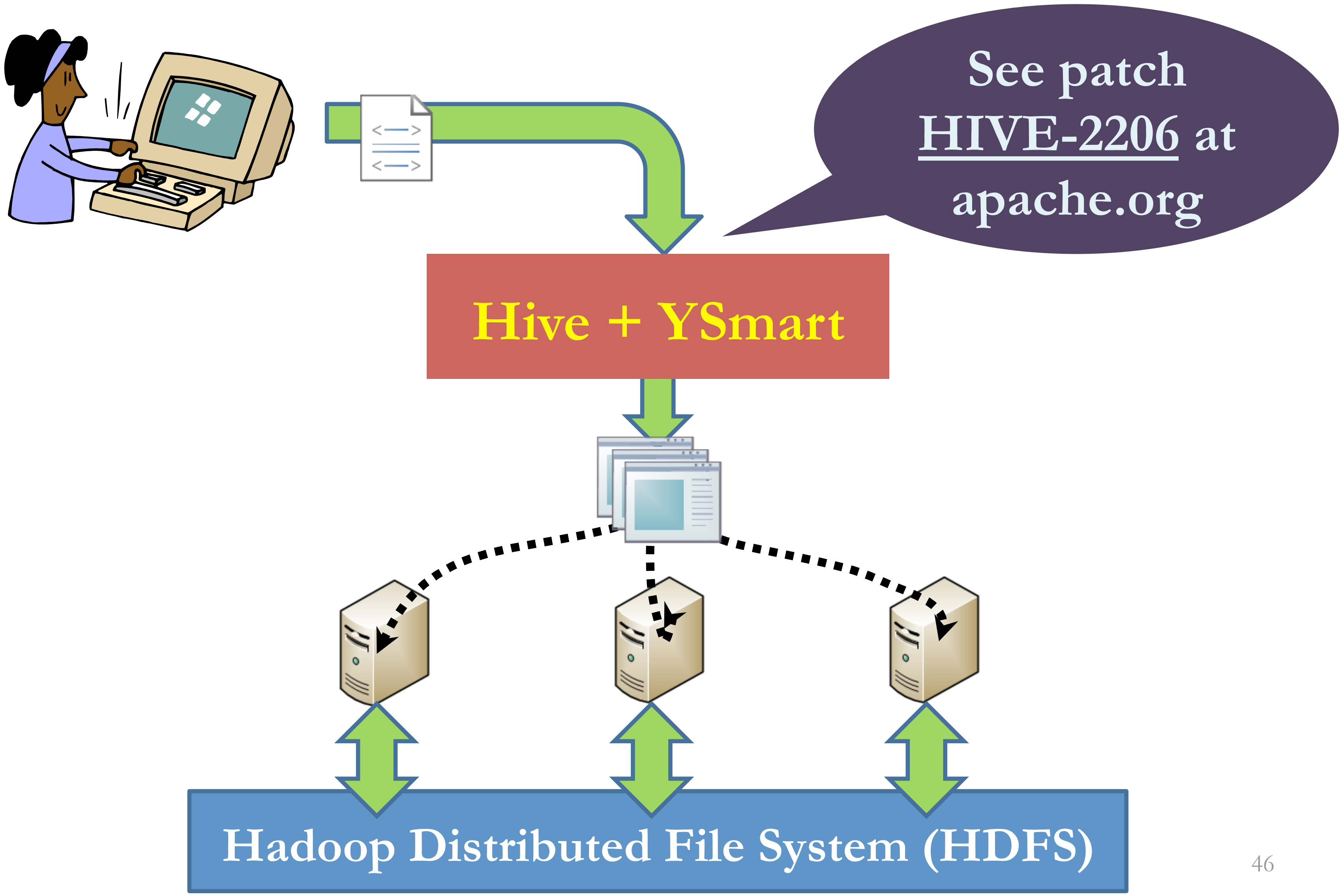
A typical query in production clickstream analysis: *"what is the average number of pages a user visits between a page in category '**X**' and a page in category '**Y**'?"*



In YSmart JOIN1, AGG1, AGG2, JOIN2 and AGG3 are executed in a single MR job

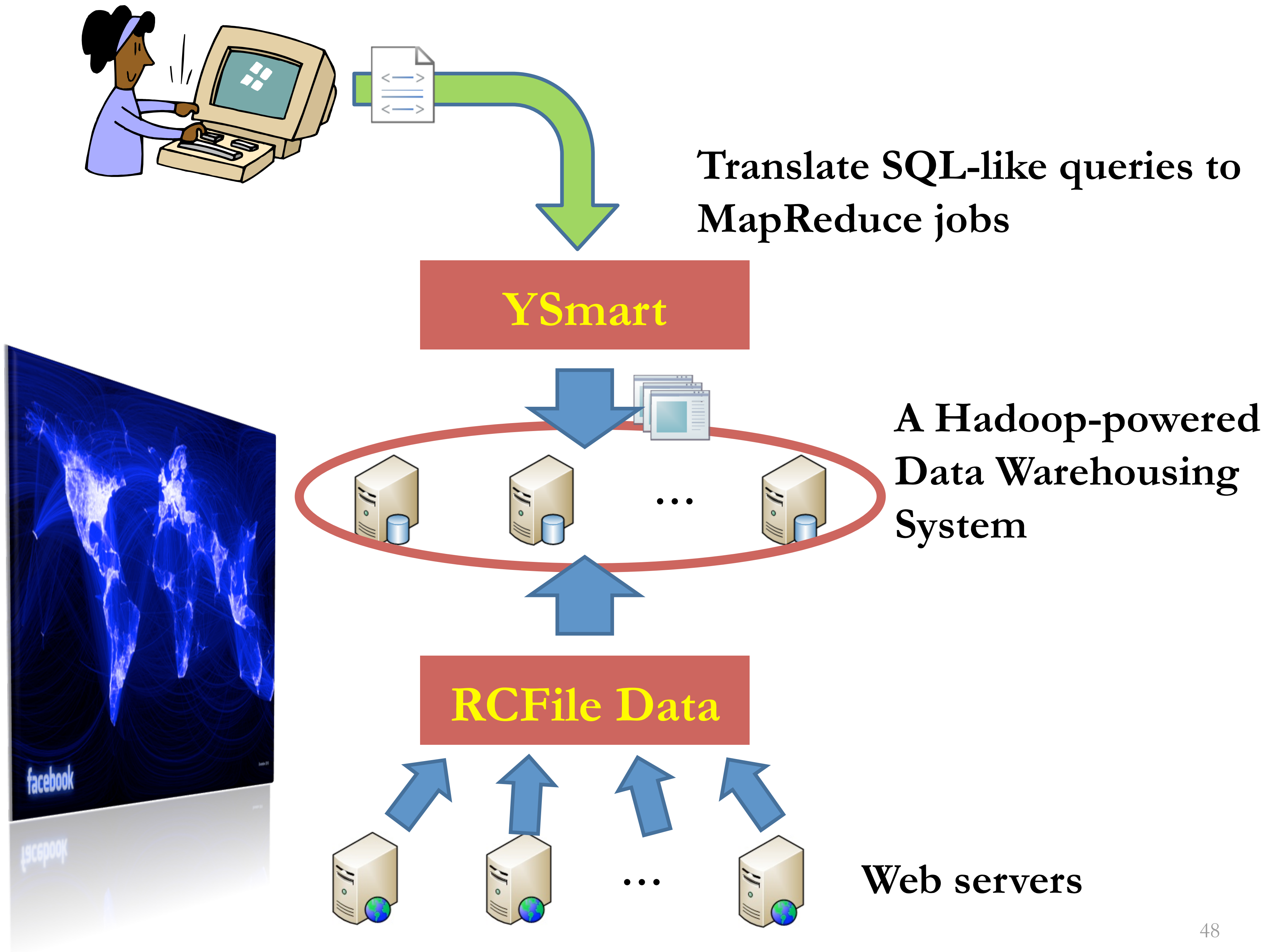


YSmart in the Hadoop Ecosystem



Summary of YSmary

- YSmart is a correlation-aware SQL-to-MapReduce translator
- Ysmart can outperform Hive by 4.8x, and Pig by 8.4x
- YSmart is being integrated into Hive
- The individual version of YSmart will be released soon


Translate SQL-like queries to MapReduce jobs
YSmart
A Hadoop-powered Data Warehousing System
…
RCFile Data
…
Web servers
facebook

Conclusion

- We have contributed two important system components: RCFile and Ysmart in the critical path of Big Data analytics Ecosystem.
- The ecosystem of Hadoop-based big data analytics is created: Hive and Pig, will soon merge into an unified system
- RCFile and Ysmart are in the critical path in such a new Ecosystem.

Thank You!